

Can we use crop modelling for identifying climate change adaptation options?

Marc Corbeels^{a,b,*}, David Berre^b, Leonard Rusinamhodzi^a, Santiago Lopez-Ridaura^c

^a CIMMYT, Sustainable Intensification Program, P.O. Box 1041-00621, Nairobi, Kenya

^b CIRAD, UPR-Agro-Ecology and Sustainable Intensification of Annual Crops, University of Montpellier, Avenue Agropolis, 34398 Montpellier, France

^c CIMMYT, Sustainable Intensification Program, P.O. Box 6-641 06600, Mexico, DF, Mexico

ARTICLE INFO

Keywords:

Adaptation
Climate change
Climate models
Crop modelling
Crop yield
Uncertainty

ABSTRACT

Climate model projections coupled with process-based crop models are advocated for assessing impacts of climate change on crop yields and for informing crop-level adaptations. However, most reported studies are vague on the choice of the global circulation models (GCMs) for climate projections, and on the corresponding uncertainty with this type of model simulations. Here we investigated whether climate-crop modelling can be used for identifying crop management-level adaptation options. We focused our analyses on a case study for maize in southern Africa using the APSIM crop growth model and projections from 17 individual climate models for the period 2017–2060 for the contrasting representative concentration pathways 2.6 and 8.5. Intensification of nitrogen fertiliser use (from 30 to 90 kg N ha⁻¹) was simulated as an example of a crop management-level adaptation to climate change. Uncertainties in crop yield predictions were about 30 to 60%, i.e. larger than expected crop responses to most management-level interventions or adaptations. Variation in simulated yields was caused by inter-seasonal rainfall variability and uncertainty with climate models. Some GCMs resulted in significantly different maize yield predictions, without any clear pattern across sites. Given these high uncertainties, we argue that crop modellers should be cautious when informing future crop management adaptation strategies based on climate-crop model ensembles. A better use of crop models is the simulation of crop responses to current weather variability aiming at the identification of crop management practices for coping with climate variability. Promising practices can then be evaluated with farmers on their feasibility over a range of plausible future biophysical and socio-economic farming conditions.

1. Introduction

Climate change will affect crop production (Lobell and Gourdji, 2012). To study this and to quantify the effects, process-based crop growth models driven by projections of future weather are commonly used (e.g. Challinor et al., 2009a; White et al., 2011). The main source of weather projections are the Coupled Model Intercomparison Project -Phase 5- (CMIP5) model simulations (Ramirez-Villegas et al., 2013). The global circulation models (GCMs) used for these simulations are, however, highly complex and contain many inherent uncertainties (Mearns, 2010). They have resolutions typically of the order of a hundred kilometres, disparate from crop growth models that operate at the smaller scale of the field. To project local climate change that can be used with crop models at field scale, data from GCMs are downscaled using a variety of methods (e.g. Fowler et al., 2007). This entails further uncertainties and potential bias in projections (Wilby et al., 1998; Ramirez-Villegas and Challinor, 2012).

A growing number of studies use local climate model projections coupled with crop growth models to inform crop management-level adaptation options to climate change, such as altering planting dates and densities, cultivars and crop species, fertiliser regimes and crop rotations or associations, and quantify their impact on crop yields (Fig. 1) (e.g. Challinor et al., 2009b; Traore et al., 2017; Waha et al., 2013). Matthews et al. (2013), for example, argued that crop modelling can contribute to climate change adaptation by identifying which future crop management practices will be appropriate.

Most reported studies that assess impacts of climate change on crop production are vague on the choice of the GCM(s) for their future climate projections. Some studies have tried to identify the ‘best’ GCM or set of GCMs for a particular region or location of interest by comparing model outputs with historical weather data (e.g. Samadi et al., 2010). However, it seems that selecting GCMs based on the quality of their climate simulation in a particular location does not result in conclusions that are systematically different from those obtained by choosing

* Corresponding author at: CIMMYT, Sustainable Intensification Program, P.O. Box 1041-00621, Nairobi, Kenya.

E-mail address: m.corbeels@cgiar.org (M. Corbeels).

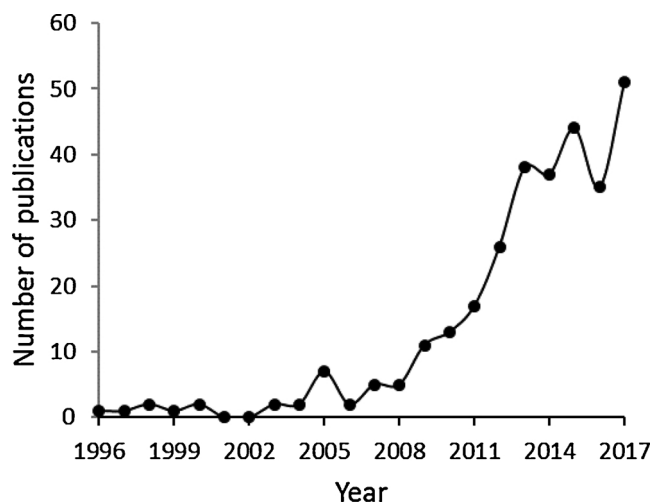


Fig. 1. Evolution of the number of papers published on studies coupling local climate model projections with crop models to inform and quantify impacts of adaptation strategies to climate change. Search string used in Scopus was: (“climate change” OR “changes in climate”) AND “crop*” AND “model*” AND “adapt*” AND (“downscaled*” OR “local*”), whereby an asterisk is a replacement for any ending of the respective term.

models randomly (Pierce et al., 2009). Moreover, a limited number of GCMs may not produce a representative range of plausible future climate projections (Ruane and McDermid, 2017). Studies increasingly use multi-GCM ensembles to cover the range of possible outcomes and to deal with uncertainties in future climate projections (Challinor et al., 2009b; Guan et al., 2017). The variability of the results from the models in the ensemble is a measure of the uncertainty as to how to model the system.

To investigate the extent to which GCMs can be used for estimating future crop yields, and more specifically, for identifying local crop management-level adaptation options to climate change, we used climate projections from 17 individual climate models that were part of the IPCC's Fifth Assessment Report (CMIP5; IPCC, 2013) (Table S1 in the Supplementary materials). We focused our analyses on simulating maize (*Zea mays* L.) grain yields at four locations in southern Africa, representing different agro-ecological conditions. Maize is the major staple food crop in that region, mainly produced with low level of nutrient inputs by smallholder farmers. Southern Africa is one of the hotspot for climate change in Africa, where climate change has been predicted to severely impact food security (Lobell et al., 2008).

2. Methods

Four sites were selected in southern Africa where long-term field experiments with maize are being conducted by CIMMYT (International Maize and Wheat Improvement Centre) (Table S2, Supplementary materials). These are: the Monze Farmer Training Centre, Zambia (16°14'27"S, 27°26'31"E, 1108 m), the Sussundenga Research Station, Mozambique (19°19'1"S, 33°14'27"E, 608 m), the Chitedze Research Station, Malawi (13°58'22"S, 33°39'14"E, 1145 m), and the Domboshawa Research Station, Zimbabwe (17°36'25"S, 31°8'27"E, 1543 m). The climate at the sites is tropical wet and dry (Aw, Köppen Climate Classification) with a unimodal rainfall pattern. Average annual rainfall is 750 mm at Monze, 1090 mm at Sussundenga, 960 mm at Chitedze and 880 mm at Domboshawa. Soils are Lixisols (Domboshawa and Sussundenga) and Luvisols (Chitedze and Monze), with distinct plant available water capacities, and fertility levels as indicated by the different soil carbon contents (Table S2, Supplementary materials). A detailed description of sites and experiments can be found in Thierfelder et al. (2013).

Simulated downscaled weather data (solar radiation, maximum and minimum temperature, and rainfall) for the four sites were obtained

using the MarkSim GCM tool (<http://gisweb.ciat.cgiar.org/MarkSimGCM>, Jones and Thornton, 2013). MarkSim is a spatially explicit daily weather generator that uses a third order Markov chain process to generate daily rainfall, radiation, and temperature. The simulated period was 2010–2060 for the highly contrasting representative concentration pathways (RCPs) 2.6 (lowest emissions) and 8.5 (highest emissions). Mean seasonal temperature and cumulative seasonal rainfall were calculated based on a pre-defined length of the cropping season, i.e. from the 1st October to the 31st May of the following year.

We used the crop model APSIM, version 7.5 (Agricultural Production Systems sIMulator). APSIM simulates crop development and growth at a daily time step as a function of weather conditions, soil properties and management practices, such as chemical fertiliser and organic matter application, planting density and date, cultivar characteristics and tillage (through simulated soil water and nitrogen limitations to plant growth). A detailed description of the model can be found in Keating et al. (2003). The model was parameterized for maize growth (medium-duration cultivars, i.e. with a growing cycle of ~120 days) at the four sites using the data from the long-term experiments (Thierfelder et al., 2013). The APSIM maize cultivar-specific parameters are listed in Table S3, Supplementary Materials. The parameterized APSIM model was then used to simulate the response of maize to climate change at the four sites for the period 2017–2060 under the two emission scenarios, RCP2.6 and 8.5. Two levels of nitrogen fertilisation were simulated: 1) 15 kg N ha⁻¹ at sowing and 15 kg N ha⁻¹ as topdressing 35 days after sowing, and 2) triple dose, i.e. 45 kg N ha⁻¹ at sowing and 45 kg N ha⁻¹ as topdressing. The model was reinitialised at the start of each year's run to make the simulations independent, i.e. for each year the soil water, carbon and nitrogen variables were reset to the initial values. Sowing date was defined as the last day of three continuous days with rainfall accumulation of 20 mm within the defined sowing window of 1 October to 31 December. The crop response to CO₂ was not included, because the CO₂ fertilisation effect on photosynthesis in C4 crops is minor and the secondary effect of reducing crop transpiration is not well captured in crop growth models such as APSIM (Durand et al., 2018). For all simulations, CO₂ concentrations were held constant at 330 ppm.

GCM effects on mean seasonal temperature, cumulative seasonal precipitation and simulated maize grain yields were estimated using ANOVA procedures and pairwise comparisons (Tukey's HSD test at $P < 0.05$). A factorial decomposition of the APSIM model response was calculated using a general linear model with fixed terms to determine how sensitive the simulated yield output is with respect GCM, emission scenario, year (cropping season) and management (nitrogen fertilisation) for each location. A sensitivity index (SI) for a factor or interactions of factors was calculated as the ratio of the sum of squares associated with the factor or interaction of factors over the total sum of squares of simulated yield data, i.e. the total variability in the model responses (see equations in Table S4, Supplementary materials). The analyses were done with PROC GLM in SAS (version 8.02).

3. Results

3.1. Climate change predictions

Predicted changes in seasonal mean temperature were highly variable largely depending on the GCM used and the study site. Overall, across the four sites they varied under RCP2.6 from -0.2 °C for BCC-CSM1-1 at Monze to $+1.5$ °C for GFDL_CM3 at Domboshawa, and under RCP8.5 from $+1.0$ °C for BCC-CSM1-1 at Domboshawa to $+3.0$ °C for MIROC-ESM at Domboshawa (Fig. 2). As expected, temperatures were predicted to become warmer under RCP8.5 compared with RCP2.6. The variation in temperature changes for a given GCM was higher in Domboshawa and Monze than in Chitedze and Sussundenga, as indicated by the size of the circles in Fig. 2. Predicted changes in seasonal

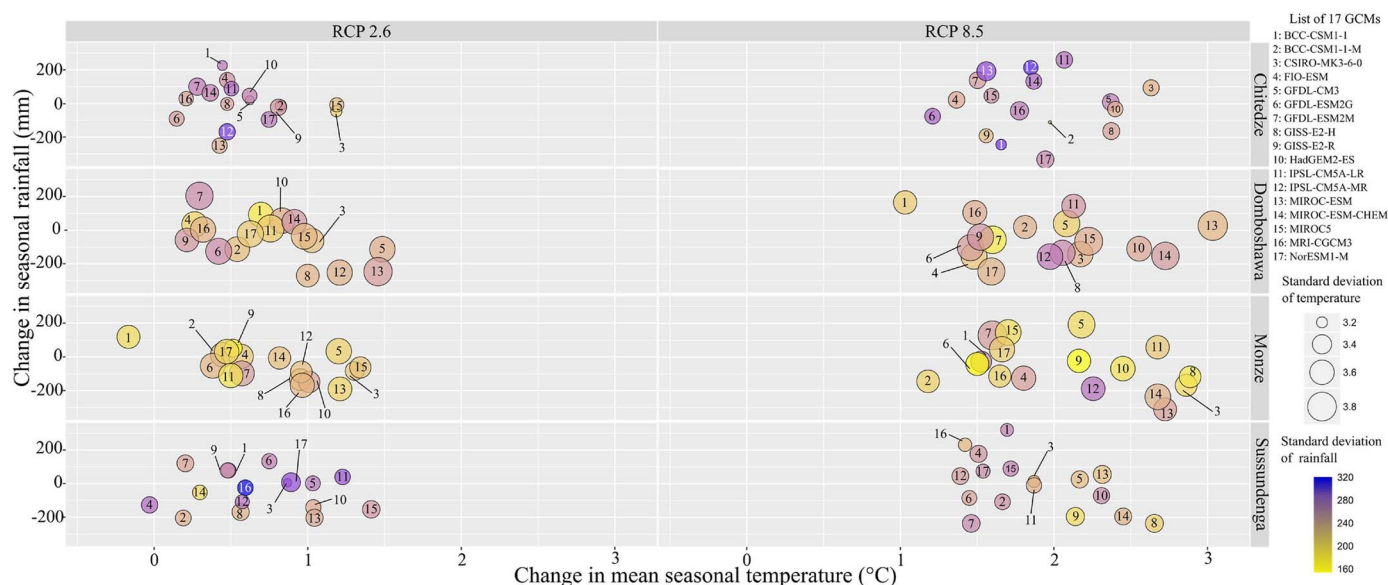


Fig. 2. Changes in mean seasonal temperature and seasonal rainfall predicted at the four study sites for the RCP2.6 and RCP8.5 emission scenarios between future (2051–2060) and baseline (2010–2017) periods for 17 global circulation models (GCMs). Numbers in or near the circles refer to the GCMs. The circle size gives the standard deviation in projected changes in temperature, the colours indicate the standard deviation in projected changes in rainfall.

rainfall also varied largely depending on the GCM, under RCP2.6 from -270 mm (GISS_E2_H at Domboshawa) to $+226$ mm (BCC-CSM1-1 at Chitedze), and under RCP8.5 from -332 mm (NORESM1-M at Chitedze) to $+320$ mm (BCC-CSM1_1 at Sussundenga). Predicted rainfall changes tended to become more variable under RCP8.5 compared with RCP2.6. The variation in predicted rainfall changes for a given GCM was in general higher in Chitedze and Sussundenga than in Domboshawa and Monze as shown by the colours of the circles in Fig. 2. There were significant ($P < 0.05$) differences in predicted seasonal mean temperature and seasonal rainfall between GCMs (Figs. S1, S2, Supplementary materials), but without any consistency across the different sites, i.e. it was not possible to identify ‘wet’ and ‘hot’ GCMs, or ‘dry’ and ‘cold’ GCMs across the four study sites (Fig. 2).

3.2. Climate change impacts on maize yields

To assess the projected climate change impacts on maize productivity at the four sites, we used the cropping system model, APSIM v7.5 (Keating et al., 2003), as an example of a process-based crop growth model. The APSIM model was calibrated for each site. Simulated total aboveground biomass and grain yields from the calibrated model reproduced relatively well the observed data (Thierfelder et al., 2013) across the four sites with root mean square errors (RMSEs) of respectively 2.28 and 1.26 t ha^{-1} (Fig. S3, Supplementary materials).

Simulated future (2017–2060) maize grain yields varied widely per location, reflecting their different agro-ecological conditions. Yields were highest at the more fertile Chitedze site and lowest at the low fertile Sussundenga and Domboshawa sites (Fig. 3). Predicted yields declined over time except for the RCP8.5 scenario at Sussundenga for the low nitrogen fertilisation dose of 30 kg N ha^{-1} . Simulated yield decline was in general larger at the more fertile sites and with the high dose of nitrogen fertilisation (90 kg N ha^{-1}). As expected, yield decline was also larger under the high emission scenario RCP8.5 than under the low emission scenario RCP2.6, except for the low fertile Sussundenga site with low nitrogen fertilisation for which simulated yield trends under RCP2.6 and RCP8.5 were similar, and close to zero. With no clear positive or negative trend in projected change in rainfall, the negative yield trends can mainly be explained by the rising projected temperatures (Fig. 2). With the APSIM model, the main reason for lower yields with increased temperatures is the reduction of the time to flowering,

thereby reducing the effective period of light interception and photosynthesis, resulting in reduced biomass and assimilate accumulation before translocation to grain (Traore et al., 2017).

3.3. Uncertainty in climate change impacts

The coefficient of variation (CV) in maize grain yield projections using the 17 GCMs for the 2017–2060 period varied from 32 to 64% depending on site (Table 1). Variations arise from inter-seasonal rainfall variability and from uncertainty with climate models (see below) and, to a lesser extent, from projected climate change (see Figs. 3 and S4, Supplementary materials). The highest yield variation was at Domboshawa, almost twice that of the other sites. Simulated yields at this site were low with relatively high absolute inter-seasonal variability (Fig. S4, Supplementary materials). Emission scenario had a small effect on the CV of simulated yields, whilst the CV slightly increased with higher simulated nitrogen fertilisation, except for the Sussundenga site. The latter is a consequence of the high yield response to nitrogen fertilisation in absolute terms.

Simulated maize grain yields differed between GCMs, indicating high uncertainty arising from the use of different GCMs. For example, when considering mid-century (2041–2060) projections, results from ANOVA with pairwise comparisons using Tukey’s HSD test showed significant differences in simulated yields between some GCMs at three of the four sites (Fig. 4), without any clear trends.

3.4. Variable responses to crop management

As an example of a crop management-level adaptation practice, we simulated intensification of nitrogen fertiliser use (from 30 to 90 kg N ha^{-1}). Increased nitrogen fertilisation may increase rainfall-use efficiency of crops in low-input cropping systems. The average change in simulated yield for the 2017–2060 period as a result of a $+60 \text{ kg N ha}^{-1}$ increase in nitrogen fertilisation varied from 3 to 145% depending on site (Table 2). By far, simulated responses to nitrogen fertilisation were largest at the least fertile Sussundenga site and smallest at the Domboshawa site that was constrained by low available soil water capacity (Table S2, Supplementary materials). Yield responses became slightly smaller under the high emission scenario RCP8.5 as compared to the low emission scenario RCP2.6

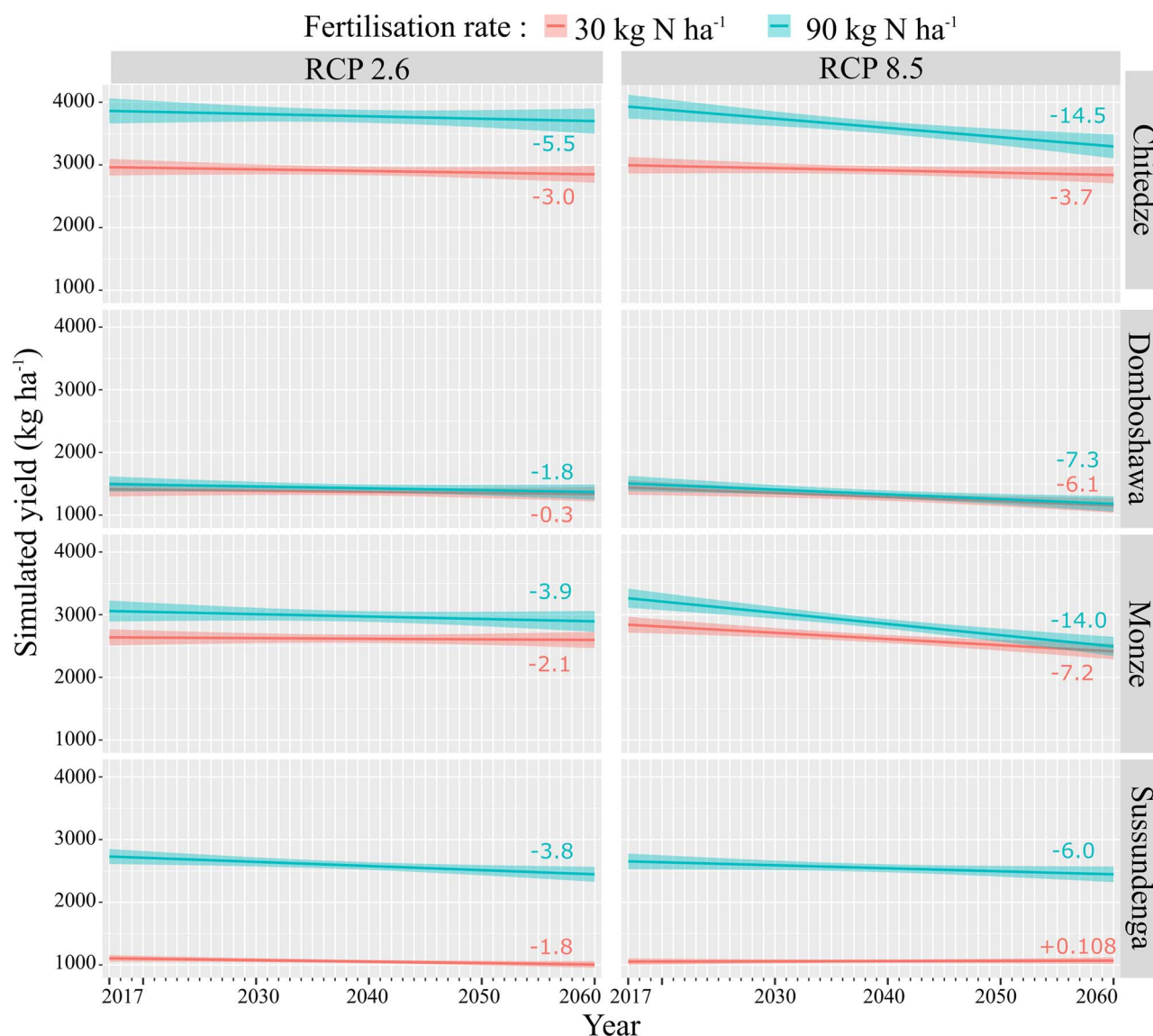


Fig. 3. Simulated trends of maize grain yields for the period 2017–2060 under two emission scenarios RCP2.6 and RCP8.5 at the four study sites with two levels of nitrogen fertilisation (30 and 90 kg N ha⁻¹). Linear least squares regression lines were fitted to simulated yields from the APSIM crop model with weather projections from 17 different GCMs. Shaded bands are the 95% confidence intervals of the regressions. Numbers (kg ha⁻¹ yr⁻¹) indicate the slope of the fitted regressions. The simulated individual data points were omitted for clarity. Fig. S4 in Supplementary materials shows corresponding boxplots of the simulated maize grain yield over the same period.

Table 1

Coefficient of variation (CV%) of simulated maize grain yield (with nitrogen fertilisation rate of 30 and 90 kg N ha⁻¹) for the period 2017–2060 at the four study sites under two emission scenarios RCP2.6 and RCP8.5.

	Emission scenario			
	RCP 2.6		RCP 8.5	
Nitrogen fertilisation (kg N ha ⁻¹)	30	90	30	90
Chitedze	33	38	32	37
Domboshawa	60	61	64	65
Monze	35	40	34	38
Sussundenga	36	33	35	35

The total variation in simulated yields because of weather variability and uncertainty with climate models (noise) was larger (or equal) than the changes in yields because of the simulated management intervention (signal) for three of the four study sites. Only at the low fertility Sussundenga site the signal:noise ratio was greater than four, indicating that only at that site the crop management adaptation option

had a robust positive impact on yield. These findings are confirmed by the results of a model sensitivity analysis with factorial decomposition of the model response (Table S5, Supplementary materials). For three sites (Chitedze, Domboshawa and Monze) the interaction GCM × year represented the most influential effect on simulated grain yield (contributing 38–44% of the total variability of the simulated yield data). Only for the Sussundenga site, nitrogen fertilisation was the most influential factor, contributing 56% of the total variability in the model response.

4. Discussion

Our findings demonstrate that the identification of crop management-level adaptation options based on linked climate-crop simulation modelling is largely hindered by uncertainties in the projections of climate change impacts on crop yields. First, variation of climate predictions is high. Their accuracy is limited by fundamental, irreducible uncertainties that are the result of structural differences in the GCMs as well as different model parametrisation and downscaling approaches (Dessai et al., 2009). We found that different GCMs gave largely

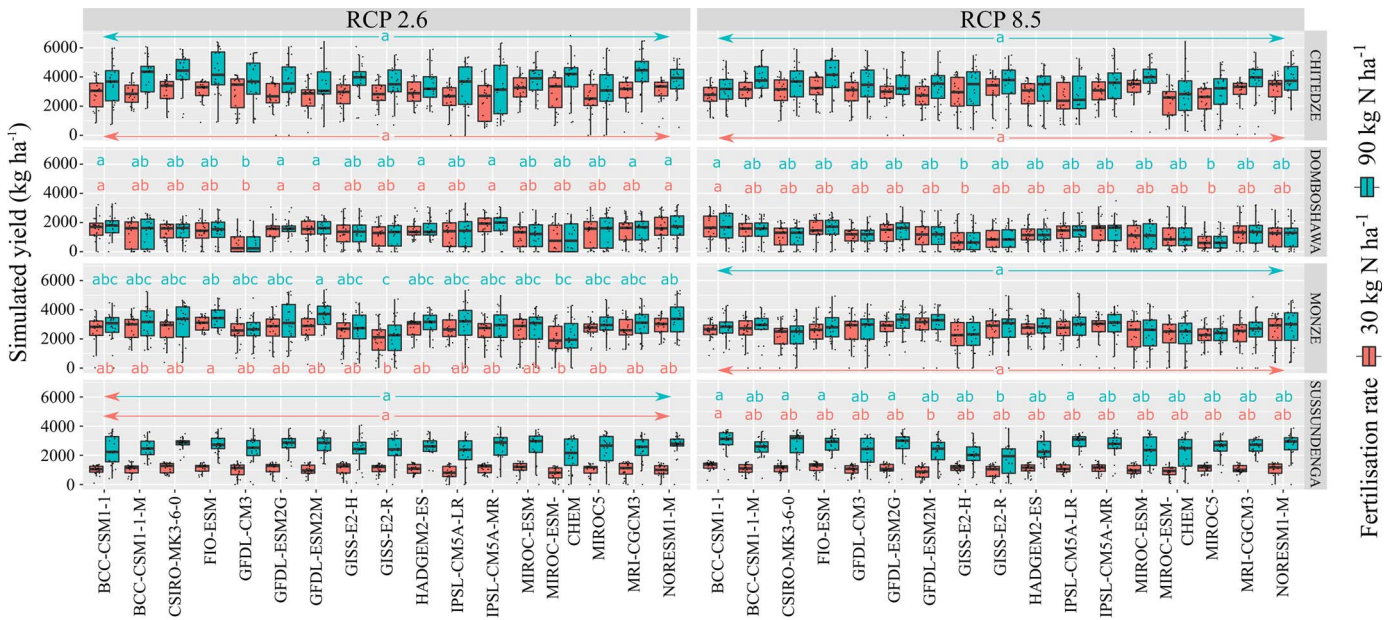


Fig. 4. Boxplots of simulated maize grain yields using the APSIM crop growth model for the 17 GCMs during the period 2040/2041–2059/2060 under climate scenarios RCP2.6 and RCP8.5 with two levels of nitrogen fertilisation (30 and 90 kg N ha⁻¹) at the four study sites in southern Africa. Upper and lower edges of boxes indicate 75th and 25th percentiles, horizontal line within box indicates median, whiskers below and above the box indicate the 10th and 90th percentiles. Within each emission scenario and fertilisation level, means of boxes with the same letter are not significantly different at $P < 0.05$ in pairwise comparisons (Tukey's HSD test).

Table 2
Average increase (%) in simulated maize grain yield for the period 2017–2060 due to nitrogen fertilisation (+ 60 kg N ha⁻¹) at the four study sites under two emission scenarios RCP2.6 and RCP8.5.

	Emission scenario	
	RCP 2.6	RCP 8.5
Chitedze	30	24
Domboshawa	4	3
Monze	14	10
Sussundenga	145	140

different results, without any clear pattern (Figs. 2 and 4, S1 and S2, Supplementary materials). Besides, projections of greenhouse gas emissions are used that are considered as representative of future socioeconomic, technological and political development scenarios. These projections of impacts of human action on emissions and climate are inherently highly uncertain. Over the last decade improvements have occurred in climate change modelling, but progress remains relatively slow (Ramirez-Villegas et al., 2013; Knutti and Sedláček, 2012), and it is expected that climate projections will remain highly uncertain at the spatial (and temporal) scales needed for crop growth simulation modelling (Dessai et al., 2009).

Second, there is also large uncertainty in simulating the responses of crops to changing climate as a result of the different structures, and input data and parameters of crop models (Asseng et al., 2013; Tao et al., 2018). Consequently, considerable differences in yield projections exist between multiple crop models (Rotter et al., 2011). Besides, crop models often lack key processes (e.g., physiological plant responses to extreme temperatures) related to climate change impacts (White et al., 2011; Webber et al., 2014), as they were not built for this purpose. It has been found that uncertainties arising from using different crop models are in many cases larger than those from ensemble climate model projections (Guan et al., 2017; Tao et al., 2018). However, in other studies the opposite was found (Challinor et al., 2009b; Holzkämper et al., 2015). In our study, we calibrated the APSIM model against observed experimental data of maize grain yield and total aboveground biomass at each study site. This reduces uncertainty in the

crop model predictions (Asseng et al., 2013). Nevertheless, we acknowledge that this probably also led to compensation of model errors since crop models such as APSIM are over-parameterised, i.e. too many model parameters are estimated relative to the amount of observed data. It also means that yield projections will become far less accurate (i.e. less reliable) when the calibrated model is used for other sites than the ones it was calibrated for, or when it is used at a regional scale.

With uncertainties in future crop yield predictions of around 30–60% or more, many potential adaptation options to climate change are not identifiable or testable with crop-climate models. Most crop management-level interventions or adaptations do generally not lead to yield increases of 30–40% or more. Exceptions do however exist: in situations of e.g. severe soil nutrient deficiencies, management options and fertilizer applications that effectively tackle these deficiencies can boost crop yields by more than 100% (e.g. Chivenge et al., 2011). In these situations, the parametrisation of non-climatic factors such as chemical and physical soil characteristics becomes, however, more important than the accuracy of climate projections for reliable simulations of crop growth (Corbeels et al., 2016).

It is also evident that due to the limited capability of crop models in simulating effects of soil and crop management practices on crop yields, only a limited number of adaptation options can be informed. In general, crop models do a reasonable job in simulating potential and water-limited yields, but they are by far less accurate when it comes to simulating nutrient-limited yields or yields that are reduced by pests and/or diseases. This means that model simulations of adaption options that impact on crop yield through soil nutrient cycling and/or pest and disease dynamics are subject to an even higher uncertainty.

Since in many situations the so-called ‘top-down’ or impact approach that is based on climate change projections seems not valid for identifying crop management strategies to cope with climate change, a more successful approach may be to begin with the decision-making context by assessing the existing capacities and vulnerabilities of farmers and their communities to climate change (i.e. ‘bottom-up’ or capacity approach, Vermeulen et al., 2013). The latter approach does not require probability-based estimates of future climate, but rather a range of plausible representations that can help to better understand how the climate-related vulnerabilities can be addressed. In this

context, robust decision-making frameworks have been developed and used to identify adaptation options under conditions of deep uncertainty about the future (Lempert et al., 2006). The frameworks have been used to help with decision-making in areas such as water resources planning, coastal management and conservation planning (e.g. Weaver et al., 2013). So far, these frameworks have not been employed for identifying rural livelihood adaptations strategies to climate change.

Most of the decisions on crop management are taken by the farmer in the context of his/her production objectives and the farming opportunities and constraints. From there, farming options can be identified and proposed that are feasible and robust over a range of plausible climatic futures, without the need for detailed climate projections. Furthermore, climate change is not the only challenge for farmers, especially in Africa where e.g. limited market access and infrastructure are major constraints to food production and security. Adaptation to climate change is to a large extent also entwined with socio-economic drivers, such as globalization, economic and political priorities and demographics. The significance of climate change as driver depends to a large extent on the local context. In fact, complexities in economic and social systems may outweigh climatic uncertainties in determining possible and feasible adaptation options. The bottom-up approach will enable the assessment of trade-offs between different adaptation options to resource issues and different drivers of change (Falloon et al., 2014). For example, farm decision support tools that include both biophysical (and climate-related) and socio-economic vulnerability indicators have been developed and used in Kenya, Tanzania and Uganda for analysing, targeting and implementing selected adaptation practices (Brandt et al., 2017; Mwongera et al., 2017). A general trend observed is that by diversifying their income sources including off-farm income, farmers become less vulnerable to climate variability and change.

An efficient way to address climate change may be to focus on strategies for coping with climate variability, rather than relying on long-term climate change predictions (Challinor et al., 2009a; Cooper et al., 2008). Crop management and yields are in many regions sensitive to climate variability and most farmers have the capacity and expertise to cope with it. Farmers can adjust to climate change by making incremental adaptations based on experience in dealing with current weather variability (Washington et al., 2006). Enhancing the capacity to cope with the current weather variability is an example of a bottom-up approach for climate change adaptation. It also means that farmers can make effective adaptation decisions in the absence of detailed climate predictions.

Whilst results from GCMs and crop modelling cannot be directly used for informing local-scale adaptation options, the use of ensembles of both climate and crop models in regionally and globally oriented impacts studies can provide valuable information that can guide policy decision-making on agricultural adaptation to climate change at national and international scales (Challinor et al., 2009b; Rosenzweig et al., 2014). Several studies have shown that at larger temporal and spatial scales general trends in projections of climate impacts appear that are robust across model ensembles despite the high uncertainty (e.g. Müller et al., 2014; Dale et al., 2017 for sub-Saharan Africa) and, therefore, can be valued by governments in their development programs and investments for adapting agriculture to climate change.

5. Conclusions

We conclude that crop modellers should be cautious when informing future crop management adaptation strategies based on crop model simulations driven by climate model projections, given the large uncertainties regarding model predictions. GCMs are not meant to predict future climate; they are rather destined to facilitate the exploration of possible future climatic trends. Therefore, climate models should be used in a robust and informed way i.e. with an understanding of the importance of climate uncertainty on impact estimates (Guan et al., 2017). For example, the use of crop models with climate models

can allow to draw robust conclusions on climate change impacts on crop yields at a regional scale (e.g. Roudier et al., 2011). However, a single analysis of the most likely adaptation for a given location is highly doubtful, as model uncertainties may be in many situations too high. Uncertainty sufficiently small to enable meaningful predictions will vary according to the location and type of adaptation studied.

Acknowledgements

The study was financially supported by the twin postdoc program between the French Agricultural Research Centre for International Development (CIRAD) through the Agropolis Foundation, and the CGIAR Research Programs on Climate Change, Agriculture and Food Security (CCAFS), and on Maize (CRP MAIZE), as part of the Agriculture Model Intercomparison and Improvement Project (AgMIP). We thank Siyabusa Mkuhlani for the generation of the weather data, and Philippe Letourmy for help with the statistical analyses.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.agrformet.2018.02.026>.

References

- Asseng, S., Ewert, F., Rosenzweig, C., Jones, J., Hatfield, J., Ruane, A., et al., 2013. Uncertainty in simulating wheat yields under climate change. *Nat. Clim. Change* 3 (9), 827–832.
- Brandt, P., Kvakić, M., Butterbach-Bahl, K., Rufino, M., 2017. How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework “targetCSA”. *Agric. Syst.* 151, 234–245.
- Challinor, A., Wheeler, T., Hemming, D., Upadhyaya, H., 2009a. Ensemble yield simulations: crop and climate uncertainties, sensitivity to temperature and genotypic adaptation to climate change. *Clim. Res.* 38 (2), 117–127.
- Challinor, A., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009b. Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. *J. Exp. Bot.* 60 (10), 2775–2789.
- Chivenge, P., Vanlauwe, B., Six, J., 2011. Does the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. *Plant Soil* 342 (1), 1–30.
- Cooper, P., Dimes, J., Rao, K., Shapiro, B., Shiferaw, B., Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? *Agric. Ecosyst. Environ.* 126 (1–2), 24–35.
- Corbeels, M., Chirat, G., Messad, S., Thierfelder, C., 2016. Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. *Eur. J. Agron.* 76, 41–53.
- Dale, A., Fant, C., Strzepek, K., Lickley, M., Solomon, S., 2017. Climate model uncertainty in impact assessments for agriculture: a multi-ensemble case study on maize in sub-Saharan Africa. *Earth's Future* 5 (3), 337–353.
- Durand, J., Delusca, K., Boote, K., Lizaso, J., Manderscheid, R., Weigel, H., et al., 2018. How accurately do maize crop models simulate the interactions of atmospheric CO₂ concentration levels with limited water supply on water use and yield? *Eur. J. Agron.* <http://dx.doi.org/10.1016/j.eja.2017.01.002>. in press.
- Dessai, S., Hulme, M., Lempert, R., Pielke, R., 2009. Do we need better predictions to adapt to a changing? *Eos Trans. Am. Geophys. Union* 90 (13), 111–112.
- Falloon, P., Challinor, A., Dessai, S., Hoang, L., Johnson, J., Koehler, A.-K., 2014. Ensembles and uncertainty in climate change impacts. *Front. Environ. Sci.* 2, 33.
- Fowler, H., Blenkinsop, S., Tebaldi, C., 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *Int. J. Climatol.* 27 (12), 1547–1578.
- Guan, K., Sultan, B., Biasutti, M., Baron, C., Lobell, D., 2017. Assessing climate adaptation options and uncertainties for cereal systems in West Africa. *Agric. For. Meteorol.* 232, 291–305.
- Holzkämper, A., Klein, T., Seppelt, R., Fuhrer, J., 2015. Assessing the propagation of uncertainties in multi-objective optimization for agro-ecosystem adaptation to climate change. *Environ. Modell. Softw.* 66, 27–35.
- Jones, P., Thornton, P., 2013. Generating downscaled weather data from a suite of climate models for agricultural modelling applications. *Agric. Syst.* 114, 1–5.
- Keating, B., Carberry, P., Hammer, G., Probert, M., Robertson, M., Holzworth, D., et al., 2003. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* 18 (3–4), 267–288.
- Knutti, R., Sedláček, J., 2012. Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Clim. Change* 3, 369.
- Lempert, R., Groves, D., Popper, S., Bankes, S., 2006. A general, analytic method for generating robust strategies and narrative scenarios. *Manage. Sci.* 52 (4), 514–528.
- Lobell, D., Gourdji, S., 2012. The influence of climate change on global crop productivity.

- Plant Physiol. 160 (4), 1686–1697.
- Lobell, D., Burke, M., Tebaldi, C., Mastrandrea, M., Falcon, W., Naylor, R., 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science* 319 (5863), 607.
- Matthews, R., Rivington, M., Muhammed, S., Newton, A., Hallett, P., 2013. Adapting crops and cropping systems to future climates to ensure food security: the role of crop modelling. *Global Food Secur.* 2 (1), 24–28.
- Mearns, L., 2010. The drama of uncertainty. *Clim. Change* 100 (1), 77–85.
- Müller, C., Waha, K., Bondeau, A., Heinke, J., 2014. Hotspots of climate change impacts in sub-Saharan Africa and implications for adaptation and development. *Global Change Biol.* 20 (8), 2505–2517.
- Mwongera, C., Shikuku, K., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., et al., 2017. Climate smart agriculture rapid appraisal (CSA-RA): a tool for prioritizing context-specific climate smart agriculture technologies. *Agric. Syst.* 151, 192–203.
- Pierce, D., Barnett, T., Santer, B., Gleckler, P., 2009. Selecting global climate models for regional climate change studies. *Proc. Natl. Acad. Sci.* 106 (21), 8441–8446.
- Ramirez-Villegas, J., Challinor, A., 2012. Assessing relevant climate data for agricultural applications. *Agric. For. Meteorol.* 161, 26–45.
- Ramirez-Villegas, J., Challinor, A., Thornton, P., Jarvis, A., 2013. Implications of regional improvement in global climate models for agricultural impact research. *Environ. Res. Lett.* 8 (2), 24018.
- Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A., Müller, C., Arneth, A., et al., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc. Natl. Acad. Sci.* 111 (9), 3268–3273.
- Rotter, R., Carter, T., Olesen, J., Porter, J., 2011. Crop-climate models need an overhaul. *Nat. Clim. Change* 1 (4), 175–177.
- Roudier, P., Sultan, B., Quirion, P., Berg, A., 2011. The impact of future climate change on West African crop yields: what does the recent literature say? *Global Environ. Change* 21 (3), 1073–1083.
- Ruane, A., McDermid, S., 2017. Selection of a representative subset of global climate models that captures the profile of regional changes for integrated climate impacts assessment. *Earth Perspect.* 4 (1), 1.
- Samadi, S., Sagareswar, G., Tajiki, M., 2010. Comparison of general circulation models: methodology for selecting the best GCM in Kermanshah Synoptic Station, Iran. *Int. J. Global Warm.* 2 (4), 347–365.
- Tao, F., Rötter, R., Palosuo, T., Gregorio Hernández Díaz-Ambrona, C., Mínguez, M., Semenov, M., et al., 2018. Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. *Global Change Biol.* 24 (3), 1291–1307.
- Thierfelder, C., Cheesman, S., Rusinamhodzi, L., 2013. Benefits and challenges of crop rotations in maize-based conservation agriculture (CA) cropping systems of southern Africa. *Int. J. Agric. Sustain.* 11 (2), 108–124.
- Traore, B., Descheemaeker, K., van Wijk, M., Corbeels, M., Supit, I., Giller, K., 2017. Modelling cereal crops to assess future climate risk for family food self-sufficiency in southern Mali. *Field Crops Res.* 201, 133–145.
- Vermeulen, S., Challinor, A., Thornton, P., Campbell, B., Eriyagama, N., Vervoort, J., et al., 2013. Addressing uncertainty in adaptation planning for agriculture. *Proc. Natl. Acad. Sci.* 110 (21), 8357–8362.
- Waha, K., Müller, C., Rolinski, S., 2013. Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid- to late-21st century. *Global Planet. Change* 106, 1–12.
- Washington, R., Kay, G., Harrison, M., Conway, D., Black, E., Challinor, A., et al., 2006. African climate change: taking the shorter route. *Bull. Am. Meteorol. Soc.* 87 (10), 1355–1366.
- Weaver, C., Lempert, R., Brown, C., Hall, J., Revell, D., Sarewitz, D., 2013. Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks. *Wiley Interdiscip. Rev. Clim. Change* 4 (1), 39–60.
- Webber, H., Gaiser, T., Ewert, F., 2014. What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa? *Agric. Syst.* 127, 161–177.
- White, J., Hoogenboom, G., Kimball, B., Wall, G., 2011. Methodologies for simulating impacts of climate change on crop production. *Field Crops Res.* 124 (3), 357–368.
- Wilby, R., Wigley, T., Conway, D., Jones, P., Hewitson, B., Main, J., Wilks, D., 1998. Statistical downscaling of general circulation model output: a comparison of methods. *Water Resour. Res.* 34 (11), 2995–3008.